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Trend Removal to Improve the Performance of a Fluctuation Sensitive Signal Processor

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ABSTRACT

The success of a fluctuation sensitive signal processor in detecting signals from submerged sources depends largely on the fluctuation character of the signal of interest. If a trend, possibly caused by multipath propagation or changes in the source-receiver distance, exists in the signal, large "apparent" amplitude fluctuations are introduced, and the fluctuation sensitive signal processor may not distinguish the signal from the noise. This paper presents a method for removing trends that may exist in the data and demonstrates the resulting improvement in the performance of such a processor.

INTRODUCTION

A processor's ability to detect a signal is greatly limited by the signal-to-noise ratio (S/N) of the signals of interest. Signals of interest could include signals detected with seismometers, sonar, radar, or magnetometers. This paper focuses on examples involving underwater acoustic signals measured by a sonar system. If the S/N is small, it may be difficult for the signal processor to extract the signal. Furthermore, if a trend exists in the signal, it may even be more difficult to extract it, because in some processors the trend increases the noise-like "appearance" of the signal. Thus, removing trends that exist in the data may improve the detection of low S/N signals. Furthermore, in a fluctuation sensitive processor, trend removal enhances the likelihood that the temporally stable signals can be attributed to a submerged source.

Acoustic background noise for some sonar systems is characterized as having high amplitude temporal fluctuations, while the amplitudes of many signals of interest generally do not vary much. Some processors discriminate against fluctuations in the data in order to enhance the performance for signals. Unfortunately, a trend in the signal, possibly caused by such things as time dependent changes in multipath propagation or source-receiver distance, can appear to some processors as a large amplitude fluctuation and make it indistinguishable from the noise. Removing these trends can aid these processors in separating signals from the background noise and, thereby, improve the performance of the system.

BACKGROUND

Measured narrow band sonar data are given in Fig. 1 to illustrate the differing characteristics of amplitude fluctuations of a signal time series and a noise time series. The x-axis represents time and the y-axis represents amplitude level in decibels (dB). During the first 67 samples the signal from a distant moving projector was being received by a towed array sonar. The projector was then turned off, and background noise was acquired for the last 33 samples. Notice that the signal has small amplitude fluctuations (less than about 2 dB), while the background noise has relatively large amplitude fluctuations (about 7 dB). Thus, by using signal processing algorithms that focus on the special features of the amplitude fluctuations of the received acoustic power, it is possible to distinguish between amplitude stable signals and noise. The objective of this study is to effectively and efficiently detrend the data in order to enhance the performance of fluctuation sensitive signal processors. One such fluctuation sensitive signal processing algorithm is Wagstaff's Integration Silencing PRocessor (WISPR) [1]. That processor is used herein to illustrate the results of detrending the data before processing.

A signal from an acoustic source can travel by way of many different propagation paths as it travels from the source to a distant receiver. Much of the amplitude fluctuation character of the received signal depends primarily on which propagation paths are taken. If the signal arrives at a receiver without encountering the surface or bottom (e.g. via the deep sound channel), there will be only small fluctuations in the time series of the signal. A temporally stable signal that travels by way of propagation paths that have many surface and bottom interactions will become amplitude modulated by the temporally varying channel and thus, have a character more indicative of noise than of a temporally stable signal. On the other hand, a stable signal that remains within the sonar channel, or has very few surface and bottom interactions, will remain relatively modulation free and temporally stable. Hence, the temporal stability of a signal can be used to infer whether or not the source is submerged. That can be a very important clue for characterizing the source.

Unfortunately, a trend in the mean level of a signal can cause it to behave statistically in a manner similar to noise, since the trend biases some of the important detection statistics in the same manner as do high amplitude fluctuations. Amplitude fluctuations can have many causes. Some of the major ones that are induced by the acoustic/oceanographic environment are:

a) interaction of the propagation paths with the irregular, moving sea surface,

b) wave induced temporal changes in the water depth above the source and the receiver,

c) forward scattering from temporally variable inhomogeneities,

d) time dependent multipath interference, and

e) internal waves.

These and other mechanisms that are responsible for generating amplitude fluctuations are discussed in detail in references 2, 3, and 4.

In addition to the fluctuation generation mechanisms listed above, trend producing mechanisms such as the source entering or leaving shadow zones or convergence zones and changes in source-receiver distances, can induce "apparent" and real amplitude fluctuations. Such apparent fluctuations can interfere with and degrade a processor's performance, since the affected signals can then have some of the same statistical characteristics as the background noise. Figure 2 illustrates how a trend in acoustic data might appear in a time series. The abscissa represents increasing time, and the ordinate represents increasing level in dB. The thick-line curve represents the trend in the data, while the other curve is the time series of the data that possesses the trend. The overall range of the data, including the trend, is about 25 dB. However, if the trend was to be removed, the range of the data would be reduced to about 10 dB. That would be more characteristic of a stable signal and could result in a significant increase in the probability of the signal processor detecting the signal.

The remainder of this paper will focus on a simple filtering technique for removing a trend in a time series and provide a quantitative evaluation of the improvement in a particular signal processor. The processor which has been chosen to illustrate the improvement is the WISPR processor [1] because it uses the fluctuation character of the signal compared to the fluctuation character of the noise to determine whether the signal is from a submerged source. Hence, it will be shown that it is important to remove trends in order to improve the sensitivity and the accuracy of the submerged source determination by the WISPR processor. The implication is that what is good for the WISPR processor is probably also good for other fluctuation sensitive signal processors.

There are many different types of statistics and algorithms that have been used as the basis for acoustic signal processors. The power average is probably the most common. In the calculations reported below, the average power level is referred to as AVGPR. As reported by

Wagstaff and Berrou [5], the average power is not necessarily the best statistic for some types of data, especially underwater acoustic data, since the average power level is biased towards the higher amplitude levels. An attractive statistic for acoustic data for some S/N enhancement applications are and submerged source signal identification is the WISPR level. Wagstaff [1] has also shown that a difference statistic, herein referred to as the DELTA level, is a good statistic for detecting stable tonals. Such designation is sometime important, because some amplitude stable signals are known to be due to a source that is submerged. DELTA is obtained by subtracting the WISPR level from the AVGPR level. Thus,

$$\text{DELTA} = \text{AVGPR} - \text{WISPR}. \tag{1}$$

DELTA can also be used as a measure of the fluctuation content of a time series.

In the results that follow, DELTA will be used as the detector of amplitude fluctuations. When the signal is well behaved (i.e. the signal does not vary much in amplitude), DELTA will be small (e.g. less than 1 or 2 dB). However, a trend in the signal can cause the amplitude fluctuations to appear to be larger than they actually are, and the signal can appear as noise to the processor. In such a case, DELTA would be relatively large (e.g. about 5-10 dB). Removing trends that may exist in the mean level of the signal and noise can improve the processor's ability to distinguish between the signal and the noise by significantly reducing the DELTA for signal, but not for noise. A simple and effective method for filtering out a trend in a time series and producing a corresponding zero mean output time series is given by the following equation for a running filter:

$$X_i' = X_i - \frac{1}{2n+1} \sum_{j=i-n}^{i+n} X_j , \quad i = n+1, n+2... \tag{2}$$

where X_i is the the point in a signal or noise level time series (in dB),

X_i' is the corresponding element of a zero mean signal or noise level time series (also in dB),

$2n+1$ is the length of the running filter.

Equation 2 utilizes a sliding decibel window averaging technique to remove a trend in a time series. It is nonlinear because the values are in decibels, not power. The size of the window is variable. The time series of the decibel levels in the filter window are summed and an average decibel level is obtained. A new data set is created by substituting this average level for the midpoint of the window of the original data. This procedure is repeated for the entire data set by sliding the window in time by one point after each substitution. Finally, the new set of data points is subtracted from the original set to obtain a zero mean level time series that has the trend removed.

Figure 3 gives a functional block diagram of the method used for the current analysis, including removing trends that exist in a data set. Since each point on an averaged spectral plot represents the average of the time series for a particular frequency bin, the detrending procedure must be repeated for the time series of each frequency bin. After the detrending method has been applied to each level time series in each frequency bin, the AVGPR and WISPR statistics are obtained. Finally, the difference, DELTA, between the a AVGPR and WISPR statistics is used to measure the success of the detrending algorithm, where a decrease in DELTA represents an improvement in the WISPR processor's performance. This procedure is followed for different filter window sizes, and the results are compared on the basis of the DELTA value and a visual evaluation of how well the detrended time series preserves the fluctuation character of the original time series (ignoring possible trends that were removed by the filter).

RESULTS

Two time series of signal and two time series of background noise, both from a common data set, were analyzed in detail (Figs. 4 and 5). Signal Case 1 (lefthand side of Fig. 4) was selected because of its dramatic trend, which causes a variation in amplitude that is on the order of 20 dB. Signal Case 2 (lefthand side of Fig. 5) was chosen to demonstrate the effect of detrending on a smaller trend, with only a 10 dB variation in amplitude. Both noise cases (righthand side of Figs. 4 and 5) were selected because they display the large amplitude fluctuations that are typical of noise.

Prior to detrending, Signal Case 1 of Fig. 4 has a DELTA of 4.89 dB. This statistic is of the same order of magnitude of what would be expected for noise, although it is known that the time series is actually a signal from a submerged source. The trend in the data is responsible for biasing the statistic upward. With the detrending algorithm set for a window size of 31, the DELTA is reduced to 0.77 dB (Fig. 4, Signal Case 1). The detrended DELTA is now indicative of a stable signal from a submerged source. Similar results due to the detrender are apparent in

Signal Case 2 (Fig. 5). Again, the DELTA is reduced significantly with the detrender set for a window size of 31. The DELTA is reduced from 2.31 dB to 0.335 dB. Hence the final statistic is more representative of an ideal signal from a submerged source.

The question now arises as to how the detrender affects the background noise. In order for the trend removal process to be of value, there should not be as significant a reduction in the DELTA for the noise as there was for the signal. Two noise cases are used to demonstrate that there is not a significant reduction in DELTA , when the detrending algorithm is used.

The first noise case (Fig. 4, Noise Case 1) has a DELTA of 7.22 dB without being detrended. With the detrending algorithm set for a window size of 31, the DELTA is reduced to 5.85 dB, which is not a significant reduction and is still indicative of noise.

The second noise case (see Fig. 5, Noise Case 2) demonstrates results similar to the first noise case. The detrending algorithm set at window size 31 produces a reduction from 5.40 dB to 4.58 dB in the DELTA . This final statistic, as in the previous noise case, is still indicative of noise. The appearance of both of the detrended noise time series suggests that the filter preserved the noise-like character of the time series, as was desired, and the test statistics indicate that the resulting noise would appear noise-like to the WISPR processor.

Both Figs. 4 and 5 show the results of detrending for filter window sizes varying from 11 to 51. Although all of the window sizes removed the trend, there are differences in the fluctuation character of the time series that result. A small window size causes an overall reduction in amplitude of the fluctuations in the time series, and does not preserve the "true character" of the details of the fluctuations. A large window size causes many of the data points to be lost, since half of the filter size is lost at the start of the time series due to the averaging technique, and half is similarly lost at the end. A window size of 31 was selected for the analysis, herein, since it more accurately preserves the original details of the fluctuations while minimizing the loss of data.

When AVGPR, WISPR, and DELTA are plotted as functions of frequency, a tri-level spectral plot is obtained (Fig. 6). In such a plot, the AVGPR statistic appears as the top curve in the spectral plot, because the average power is biased towards the higher values. The WISPR statistic, on the other hand, is biased toward the lower values. It is often about 8 to 9 dB less than the curve for the AVGPR statistic. The WISPR result is the second curve from the top of Fig. 6. The difference between these two statistics, DELTA (order of 8 to 9 dB), is plotted at the bottom of the plot to avoid confusing it with the previous two curves. A threshold of 1.5 dB for the levels in the DELTA curve has been empirically chosen (a result arrived at from processing and analyzing many data sets that contain stable submerged source signals in ambient noise) to distinguish between stable signals and background noise. A value of DELTA that is less than the threshold (1.5 dB) can be used to indicate a stable signal, and a value of DELTA, that is above the threshold can be used to indicate noise.

Figure 7 illustrates the time series plots for select frequency bins in the spectral plot of Fig. 6. These time series plots have been chosen for consideration in greater detail to demonstrate the nature of the improved results seen in Fig. 6.

The results of trend removal in the time series for both the noise and the signals in Fig. 4 and Fig. 5 were very favorable. Similarly, trend removal should show favorable results for the signals and noise in Fig. 6. When the trend is removed, using a window size of 31, there was an obvious improvement in the DELTA curve (bottom curve), since these are about four more acoustic signals in it than are appearing in the non-detrended DELTA curve (second curve from the bottom). At frequency bin A, there is an apparent signal in the AVGPR and WISPR curves (upper two curves in Fig. 6). The non-detrended DELTA curve (top DELTA curve in Fig. 6) shows this to be a stable signal, since it is below the threshold of 1.5 dB. After trend removal, that same signal in the new DELTA curve is still below the threshold (Fig. 6, frequency bin A of the bottom DELTA curve). The time series of this frequency bin (the top plot in Fig. 7) indicates that this is indeed a signal with low amplitude fluctuations. The DELTA (Δ) is below the threshold for both the non-detrended case (top curve) and the detrended case (bottom curve), but there was an improvement after trend removal, because the DELTA was reduced from 0.72 dB to 0.17 dB (see the original and detrended time series for frequency bin A in Fig. 7).

The AVGPR and the WISPR curves indicate another apparent signal at frequency bin B, but it is not below the 1.5 dB threshold in the non-detrended DELTA curve. However, the signal does pass the threshold in the DELTA curve after trend removal (Fig. 6, frequency bin B of the bottom DELTA curve). The time series of frequency bin B of Fig. 7 shows that there is a definite trend before trend removal, and the DELTA (Δ) is relatively large at 11.46 dB. After trend removal, the DELTA is reduced to 0.24 dB, which is well below the 1.5 dB threshold that indicates an amplitude stable signal.

An arbitrary noise frequency bin, C, was chosen to show that trend removal does not greatly alter the processor's performance for noise cases (make the time series more signal like and generate false alarms). Both DELTA curves in Fig. 6 indicate that there is background noise in frequency bin C. The time series of the data in this frequency bin (third plot of Fig. 7) shows a small change after trend removal with a slight reduction in DELTA from 8.99 dB to 8.07 dB. Both of these DELTA values are well above the 1.5 dB threshold and indicate that this particular frequency bin contains a time series of data that is indicative of background noise.

As a final example, consider the apparent signal at frequency bin D that does not have a DELTA curve that is indicative of a stable signal in the non-detrended DELTA curve of Fig. 6. The detrended DELTA, on the other hand, shows that this is a fairly stable signal . Again, the time series in the bottom plot of Fig. 7 shows that there is a trend in the data of frequency bin D, thus resulting in a relatively high value of DELTA. After trend removal, the DELTA was reduced from 4.69 dB to 1.48 dB and passes the test for a stable signal . Hence, removing the trend caused the DELTA curve to indicate the existence of a stable tonal signal. Without trend removal, the processor could not distinguish this signal from the noise. Furthermore, the detrended DELTA curve shows that the high level signal that is midway between bin B and bin D of Fig. 6 is stable and that there are two more stable signals near the signal at bin D that were not identified as stable signals in the non-detrended DELTA curve.

All of the signals in Fig. 6 were of sufficiently high S/N to be easily detected in the AVGPR curve. In such a case, the detrending provided no added value for increasing the S/N. The real value of detrending and the DELTA curve is in identifying those signals that, because of a high degree of amplitude stablilty, the WISPR processor can attribute them to be due to a submerged source. That very important function was significantly enhanced by detrending the data before being input to the WISPR processor.

CONCLUSIONS

The detrending algorithm significantly decreases the DELTA statistic for signals, but it does not significantly change the DELTA for background noise. Hence, the detrending algorithm can be used to remove trends in the means of both signal and noise data to increase a fluctuation sensitive signal processor's ability to identify amplitude stable signals from among the noise background.

ACKNOWLEDGMENTS

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LIST OF FIGS.

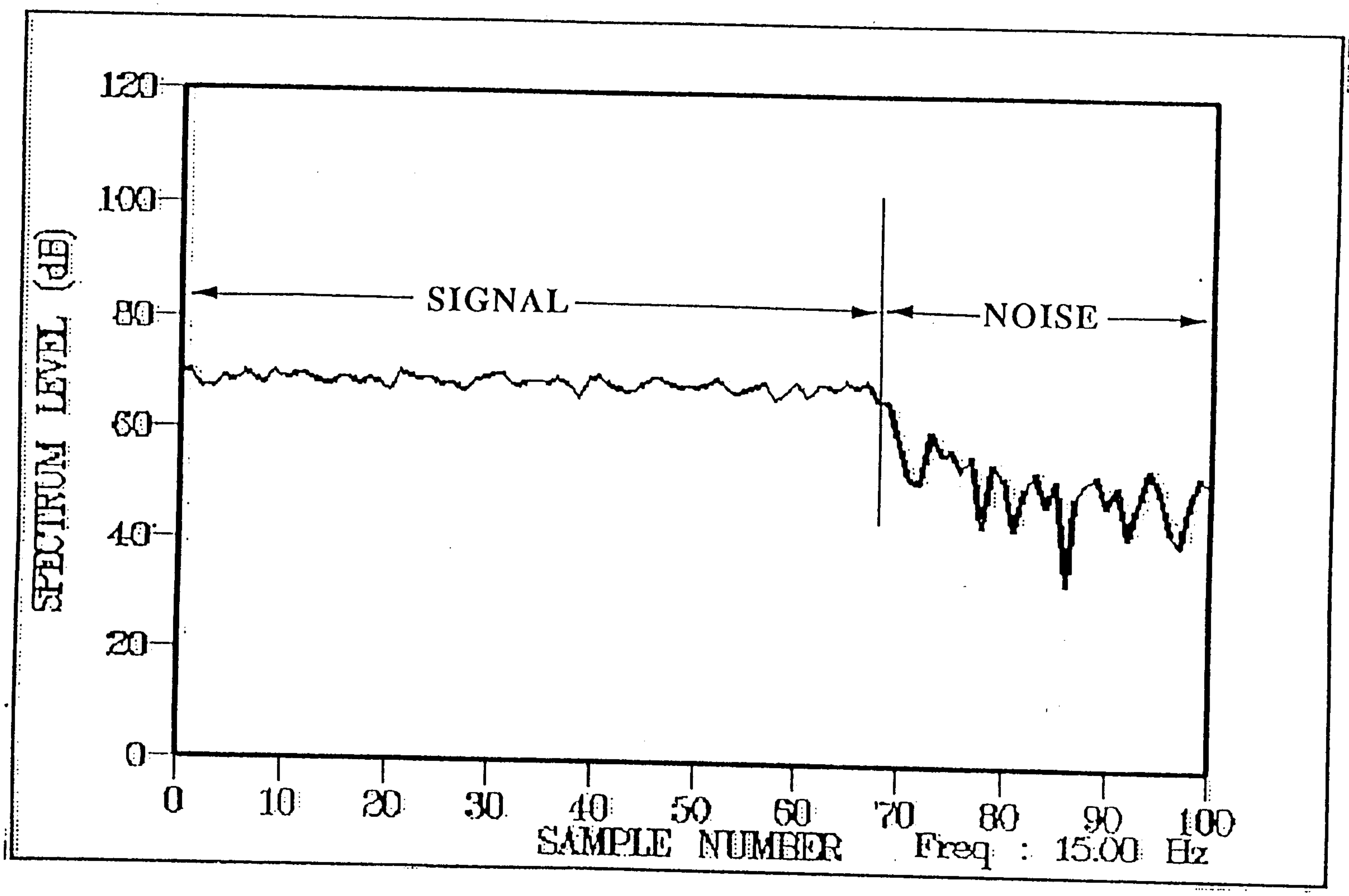

Figure 1. Acoustic data measured in a given frequency bin during a measurement exercise illustrates the differing characteristics of amplitude fluctuations of signal and noise.

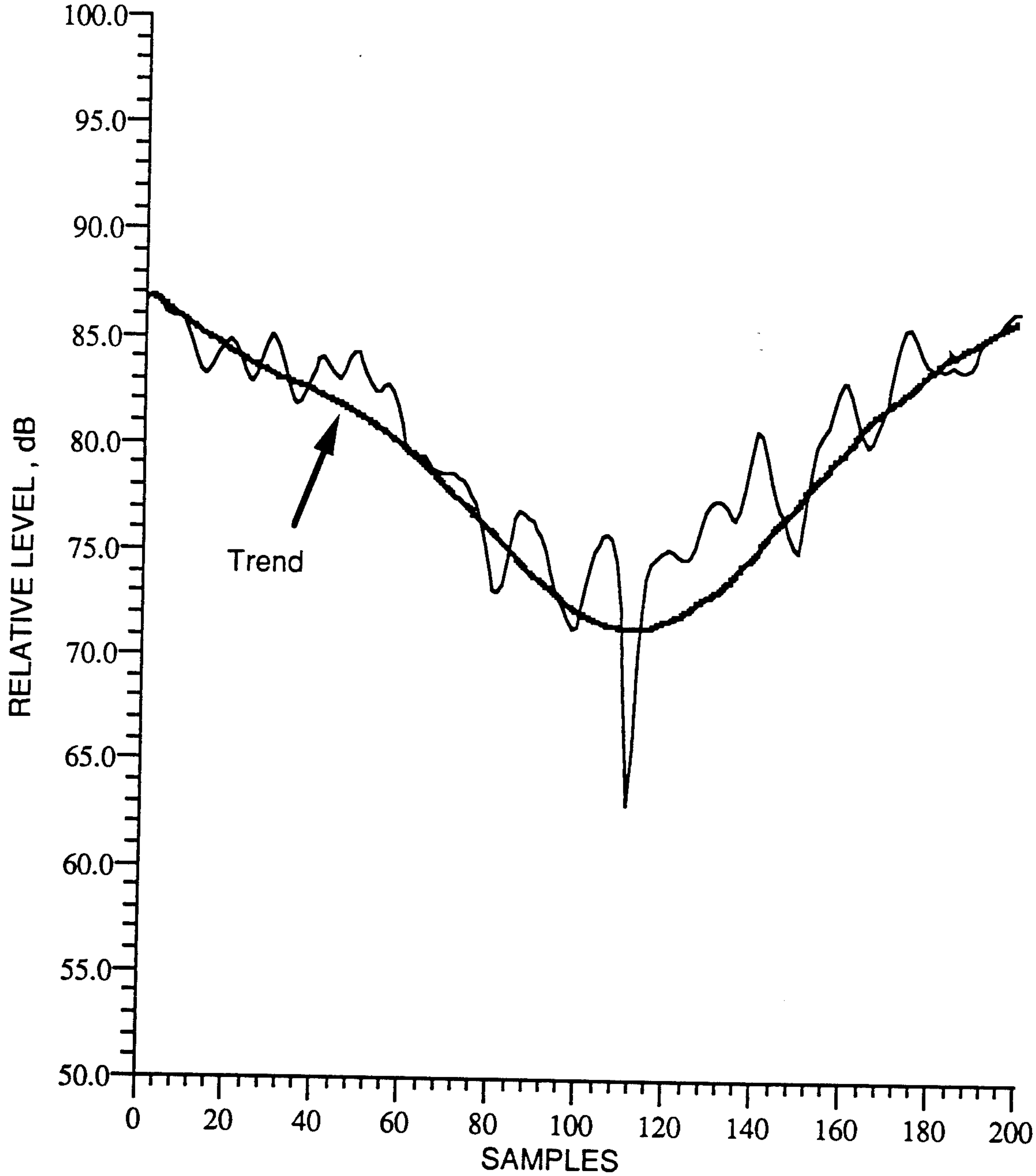

Figure 2. Time series of acoustic data (narrow curve) containing a trend (thick curve).

MEAN LEVEL TREND REMOVAL PROCEDURE

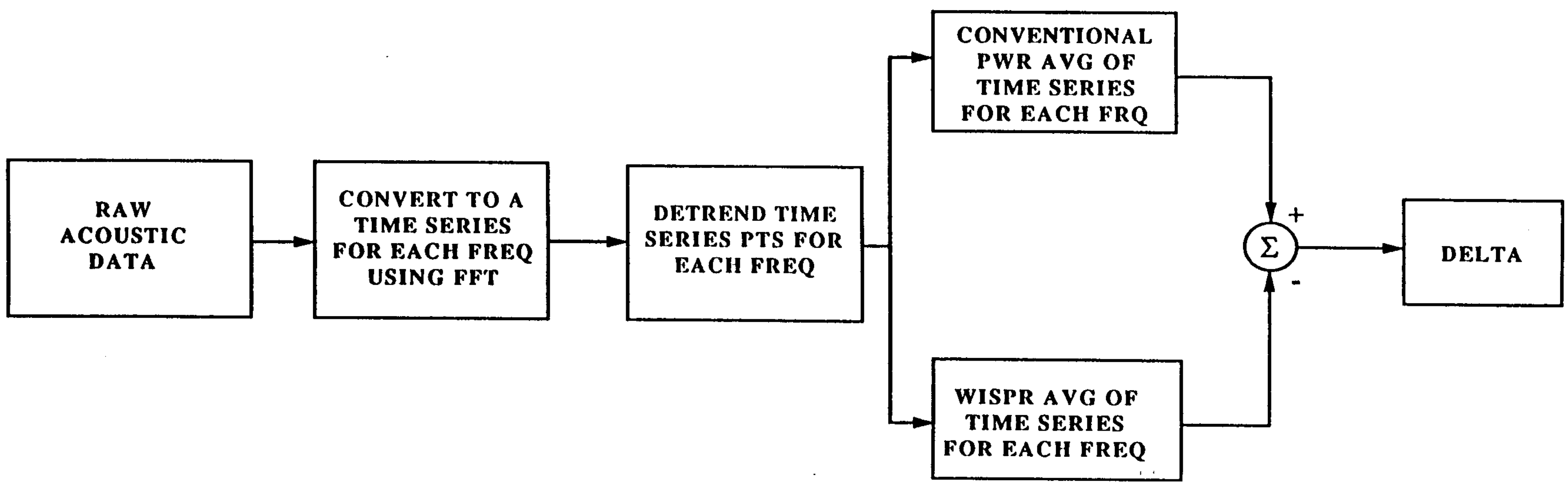

Figure 3. Functional block diagram of the method for removing a trend and testing the results.

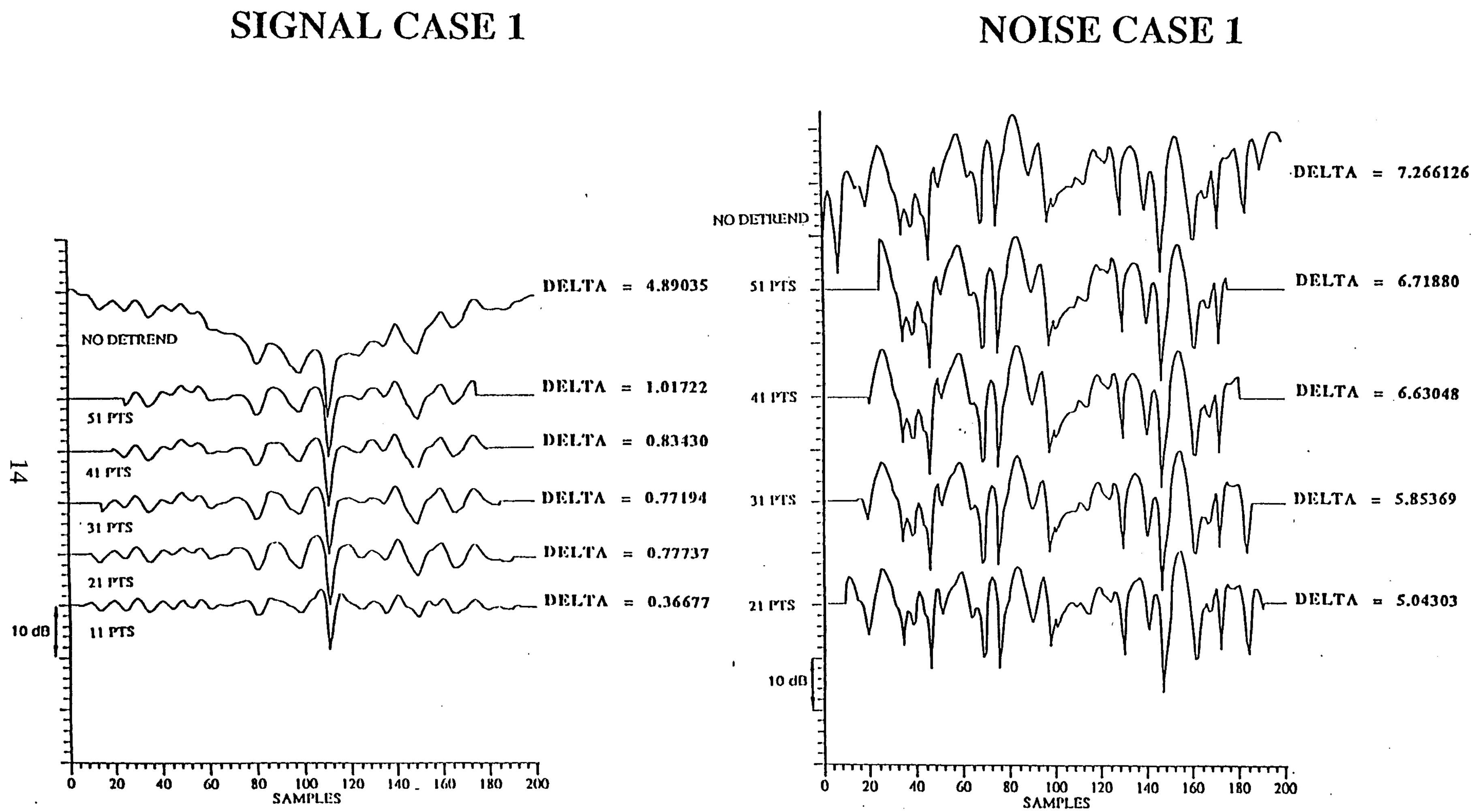

Figure 4. The effects of detrending for varying window sizes for Signal Case 1 (lefthand side) and Noise Case 1 (righthand side). DELTA quantifies the results.

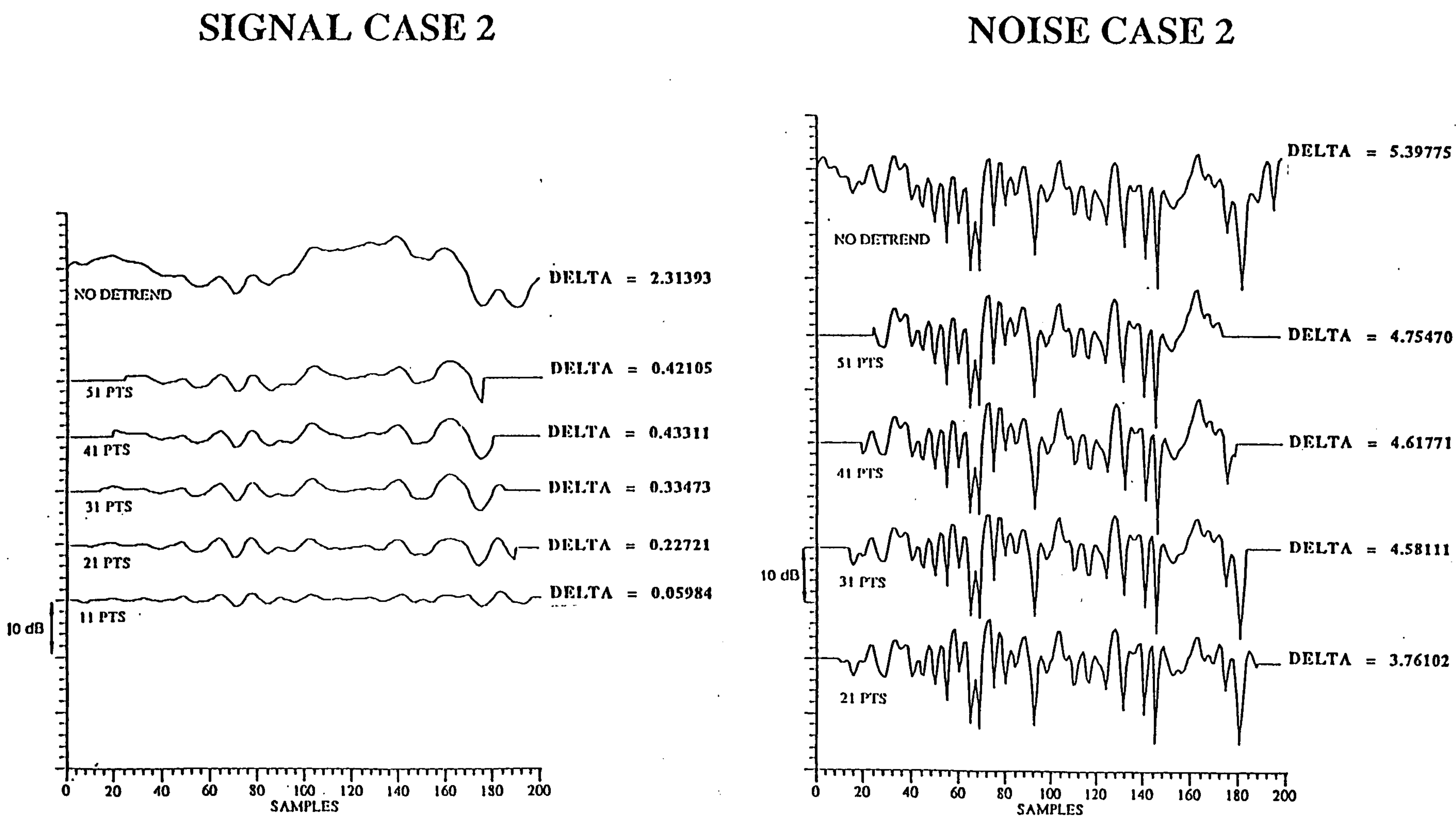

Figure 5. The effects of detrending for varying window sizes for Signal Case 2 (lefthand side) and Noise Case 2 (righthand side). DELTA quantifies the results.

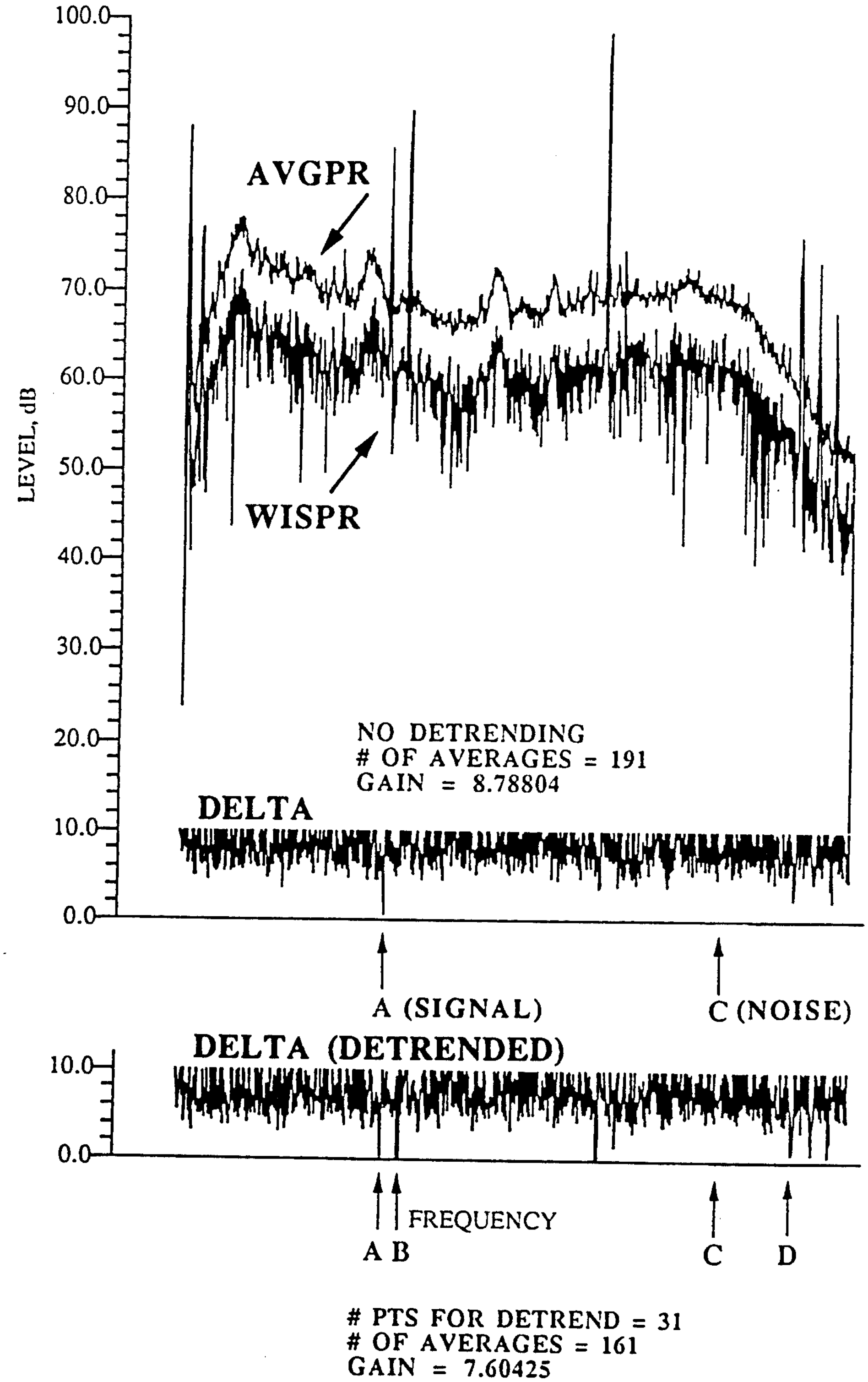

Figure 6. Average power (top curve) and WISPR spectra (second curve) and DELTA third curve), detrended DELTA (bottom curve).

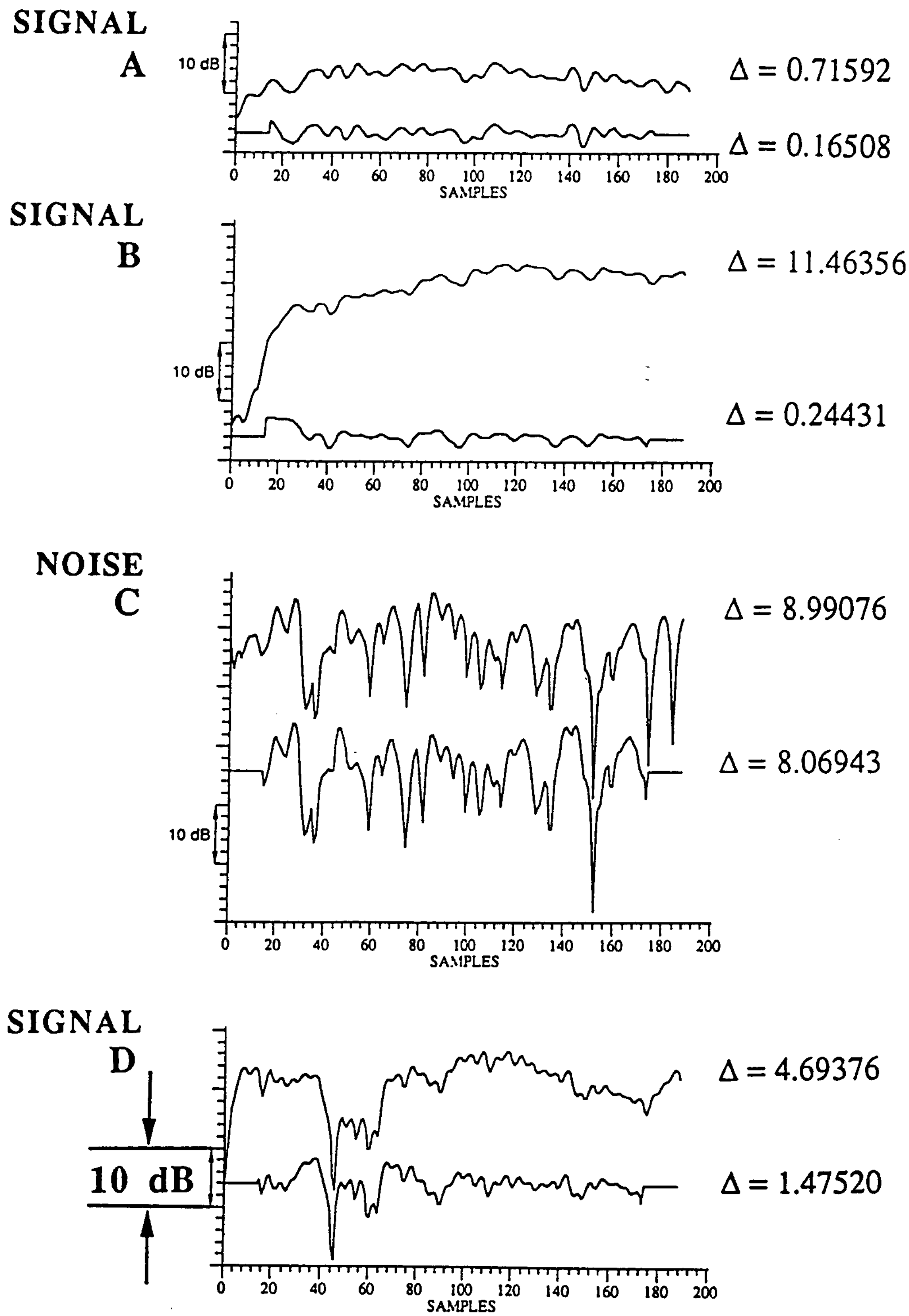

Figure 7. Original (top curve) and detrended (bottom curve) time series for three signal cases (A,B, and D) and one noise case (C) corresponding to the frequency bins indicated in Fig. 6. DELTA is represented by the symbol Δ.